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ORIGINAL RESEARCH ARTICLE

# Assessing Smart Supply Chain Risks in the Electricity Industry Using Digital Transformation

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## ABSTRACT

The study aims to assess and rank smart supply chain risks in the electricity industry by incorporating digital transformation technologies into a multi-criteria decision-making framework. The research is developmental–applied in nature and adopts a descriptive–survey design using a mixed-method approach. In the qualitative phase, semi-structured interviews with experts from the electricity industry were analyzed through thematic analysis to identify the principal supply chain risk criteria and strategic mitigation approaches. The analysis resulted in nine evaluation criteria: probability of supply disruption, severity of disruption impact, supply chain resilience, system recovery time, supply reliability, supply chain flexibility, total supply chain cost, economic efficiency of supply, and risk management cost. Three strategic responses were also identified: strengthening supply chain resilience, digitalizing and intelligently monitoring supply chain processes, and localizing and diversifying supply sources. In the quantitative phase, the Step-wise Weight Assessment Ratio Analysis (SWARA) method was employed to determine the relative importance of the identified criteria. The findings revealed that probability of supply disruption (0.232), severity of disruption impact (0.176), and supply chain resilience (0.136) were the highest-priority risk factors, followed by system recovery time, supply reliability, and supply chain flexibility. The proposed framework supports data-driven risk prioritization and demonstrates how digital transformation technologies can improve supply chain resilience, proactive risk management, and strategic decision-making in the electricity industry, thereby contributing to the development of more intelligent and sustainable digital supply chain ecosystems. **©authors**

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## Introduction

Digital transformation has fundamentally reshaped the structure of electricity supply chains, shifting them from conventional, centralized systems toward intelligent, data-driven, and highly interconnected ecosystems. Within the framework of *Energy 4.0*, the integration of advanced digital technologies—including the Internet of Things (IoT), artificial intelligence (AI), blockchain, cloud computing, and digital twins—has enabled real-time monitoring, predictive maintenance, automated decision-making, and greater operational efficiency across electricity generation, transmission, and distribution networks (Energy 4.0, 2024). These technological advances have significantly improved resource utilization, reduced operational costs, and enhanced the sustainability of energy systems. At the same time, however, they have introduced new categories of risk associated with cyberattacks, communication failures, data integrity, algorithmic bias, and the increasing dependence of operational processes on digital infrastructures. Consequently, ensuring the resilience and reliability of smart electricity supply chains has become a strategic priority for both policymakers and industry practitioners (Tubis & Poturaj, 2025).

Existing studies indicate that as the level of digitalization increases, cyber, operational, and infrastructure-related risks become increasingly interconnected, creating complex risk propagation mechanisms throughout the supply chain (Carvalhosa et al., 2024). Despite these developments, most conventional risk assessment approaches continue to rely on linear, static, and single-criterion evaluation methods that are unable to capture the multidimensional and dynamic nature of digitally enabled supply chain risks (Kolapo, 2024). Furthermore, many electricity organizations still evaluate risks independently across functional units using experience-based judgments, which limits their ability to identify cascading effects among technological, operational, economic, and security risks. Recent research emphasizes that the successful transition toward smart grids requires integrating digital technologies with systematic, data-driven, and risk-based decision-making frameworks capable of supporting strategic planning under uncertainty (Samuels, 2025). Nevertheless, a comprehensive framework that simultaneously identifies, evaluates, and prioritizes smart supply chain risks while incorporating the implications of digital transformation remains insufficiently developed in the existing literature.

Another important challenge concerns the existence of conflicting managerial objectives within smart electricity supply chains. Decision-makers are required to balance operational resilience, supply reliability, cybersecurity, economic efficiency, cost optimization, and environmental sustainability simultaneously. Because digital technologies create strong interdependencies among supply chain components, disruptions occurring in one segment can rapidly propagate across the entire network, amplifying both operational and financial consequences. Under these conditions, prioritizing risks based solely on subjective judgment or isolated performance indicators may lead to ineffective resource allocation and suboptimal strategic decisions. Therefore, there is a growing need for a structured multi-criteria decision-making framework capable of integrating technological, operational, economic, and security considerations into a coherent risk assessment process.

Accordingly, this study, entitled "Assessing and Ranking Smart Supply Chain Risks in the Electricity Industry Using Digital Transformation Technologies**,**" aims to develop a comprehensive analytical framework for identifying, evaluating, and prioritizing multidimensional risks in the smart electricity supply chain. By combining qualitative thematic analysis with the SWARA multi-criteria decision-making method, the study seeks to provide a systematic and data-driven tool that supports more effective risk prioritization and strategic decision-making in digitally transformed electricity supply chains. In addition to addressing an important gap in the supply chain risk management literature, the proposed framework contributes to the broader field of digital transformation by facilitating the development of resilient, intelligent, and sustainable energy supply chain ecosystems.

Beyond conventional supply chain risk assessment, this study is positioned within the broader context of digital transformation in the electricity industry. The increasing adoption of digital technologies, including artificial intelligence, big data analytics, the Internet of Things (IoT), cloud computing, and digital monitoring platforms, has fundamentally reshaped the way supply chain risks are identified, monitored, and managed. Consequently, developing a systematic framework for assessing and prioritizing smart supply chain risks not only supports operational resilience but also contributes to the implementation of digital transformation strategies. By integrating expert knowledge with the SWARA method, this study provides decision-makers with a structured approach for prioritizing risks in digitally enabled supply chains, thereby aligning the research with contemporary developments in digital transformation and smart industrial management

## Literature Review

### *Risk*

Risk is defined in management literature as the probability of adverse events occurring and the extent of their impact on the organization's objectives. In the supply chain, risks usually appear in a multidimensional manner, including operational, financial, technological, environmental, and strategic risks. In the electricity industry, risk is doubly important because this industry is known as critical infrastructure and any disruption can have widespread economic and social consequences. According to the ISO 31000 perspective, risk management includes identifying, analyzing, assessing, and responding to risks, which aims to reduce uncertainty in decision-making. In recent studies, energy supply chain risks, especially in the context of digitalization, have become complex and interrelated risks that do not behave linearly and require intelligent approaches to analysis (Aven, 2023; Khan et al., 2024).

### *Supply Chain*

A supply chain is a network of organizations, people, activities, information, and resources that contribute to the production and delivery of a product or service. In the electricity industry, the supply chain includes the generation, transmission, distribution, and consumption of energy, which is heavily dependent on physical and digital infrastructure. In modern models, the electricity supply chain has transformed from a linear to a networked and intelligent one, in which real-time data exchange plays a key role. This transformation has increased efficiency, but at the same time has increased the complexity of the system and its vulnerability. The theory of a resilient supply chain emphasizes that the system must have the ability to predict, absorb, and recover from disruptions (Ivanov & Dolgui, 2022). In the electricity industry, this resilience is directly related to energy security and grid stability.

### *Smart Supply Chain*

A Smart Supply Chain is an extended version of the traditional supply chain in which digital technologies are used to optimize decision-making and increase transparency. This concept is based on the integration of the Internet of Things, artificial intelligence, blockchain and big data analytics. In the smart electricity supply chain, sensors and digital systems collect real-time data on energy production and consumption and enable automated decision-making. However, this smartization has created new risks such as cyberattacks, algorithmic errors and dependence on digital infrastructure. According to the Industry 4.0 perspective, smart supply chain simultaneously increases productivity and increases system complexity, which requires advanced risk management (Kamble et al., 2024).

### *Electricity Industry*

The electricity industry is one of the most critical infrastructures of any country, on which the performance of other economic sectors depends. This industry consists of three main sectors: generation, transmission and distribution, and due to the continuous and non-storable nature of electricity, it is highly sensitive to disturbances. In complex systems theory, the electricity grid is known as a nonlinear dynamic system whose behavior depends on the interaction of multiple components. In recent years, the introduction of renewable energy and smart grids has increased uncertainty in the industry. Also, the digitalization of the electricity industry has increased the level of connectivity and, as a result, increased contagion risks. Therefore, the electricity industry requires advanced risk assessment models to maintain energy sustainability and security (IEA, 2024).

### *Digital transformation*

Digital transformation is the process of integrating digital technologies into all aspects of the organization to create new value and change the way it operates. In the electricity supply chain, digital transformation includes the use of artificial intelligence, the Internet of Things, cloud computing, blockchain and digital twins to improve decision-making and increase efficiency. The theory of digital transformation emphasizes that this process is not only a technological change, but also a structural and cultural change in the organization. In the energy industry, digital transformation has increased transparency, reduced costs and improved demand forecasting. However, recent studies show that this transformation simultaneously creates new risks, such as cyber threats and technological dependencies, that need to be managed within a smart risk management framework (Verhoef et al., 2021; OECD, 2023).

### *Risk Assessment and Ranking*

Risk assessment and ranking is a process in which risks are prioritized based on their probability of occurrence and severity of impact in order to allocate organizational resources optimally. In this area, multi-criteria decision-making (MCDM) methods such as AHP, TOPSIS, and ANP are widely used. In recent years, combining these methods with artificial intelligence and fuzzy logic has increased the accuracy of risk analysis. In the smart electricity supply chain, due to the high uncertainty and complex data, the use of classical methods alone is not sufficient and there is a need for hybrid models. Risk-Based Decision Making theory emphasizes that decisions should be made based on systematic analysis of risks and not solely on managerial experience (Zhou et al., 2023).

Hasani et al. (2025) investigated the operational risks associated with digital supply chain transformation using a hybrid multi-criteria decision-making framework combining Fuzzy ANP, ISM, and MICMAC techniques. Their findings revealed that information technology risks, supply chain management risks, and financial risks constitute the most critical barriers to successful digital transformation. The study further demonstrated that integrated data strategies and enhanced collaboration among supply chain stakeholders are the most effective mitigation approaches. However, the research focused on general digital supply chains and did not specifically address the electricity industry or provide a sector-specific risk prioritization framework.

Tubis and Poturaj (2025) conducted a comprehensive review of digital transformation in energy supply chains. They concluded that digital technologies such as IoT, artificial intelligence, blockchain, and digital twins substantially improve visibility, efficiency, and sustainability across energy supply networks. Nevertheless, increasing digitalization simultaneously introduces new cyber threats, operational vulnerabilities, and infrastructure security challenges, emphasizing the need for advanced risk assessment models capable of supporting resilient energy supply chains.

Zhang (2025) examined the relationship between supply chain digitization, risk management, and organizational resilience in energy enterprises using PLS-SEM and fsQCA. The results indicated that digital transformation enhances energy resilience indirectly through effective risk management practices. The study highlighted that organizations with stronger digital capabilities and integrated risk management systems achieve higher operational resilience and improved decision-making performance under uncertain conditions.

Ashraf et al. (2024) proposed a cognitive digital supply chain twin based on hybrid deep learning algorithms for early disruption detection. Their findings showed that digital twin technology significantly improves disruption prediction, real-time monitoring, and supply chain responsiveness. The study demonstrated the potential of intelligent digital platforms for enhancing supply chain resilience but primarily concentrated on disruption detection rather than comprehensive multi-criteria risk prioritization.

Shahidpoorfalah et al. (2024) developed a Fuzzy-VIKOR framework to assess the risks associated with adopting digital technologies in sustainable supply chain management. Their results identified the shortage of digital and information technology competencies as the most influential risk affecting sustainable supply chain performance. The study emphasized that structured multi-criteria decision-making methods provide an effective approach for prioritizing digital transformation risks under uncertainty.

Deng et al. (2024) introduced a data-driven and privacy-preserving risk assessment framework for smart grids based on federated learning. Their proposed model enabled accurate security risk assessment while preserving data privacy across distributed smart grid infrastructures. The findings demonstrated that artificial intelligence and distributed learning techniques can substantially improve cyber risk prediction and operational security in digitally connected electricity systems.

Although this study primarily focuses on smart supply chain risk assessment in the electricity industry, it is closely aligned with the emerging literature on digital transformation, virtual economies, and metaverse-enabled industrial ecosystems. The development of digital infrastructures, cyber-physical systems, Internet of Things (IoT), digital twins, and AI-driven decision support has created increasingly interconnected and data-centric supply networks that underpin virtual business environments. In such ecosystems, effective risk assessment and prioritization become essential for ensuring the resilience, reliability, and continuity of digitally integrated operations. Therefore, the proposed framework contributes not only to smart supply chain management but also to the broader discourse on digital and virtual economic systems by providing a structured decision-making approach for managing risks within technology-enabled industrial ecosystems.

The novelty of this study lies in both its theoretical and practical contributions. From a scientific perspective, unlike previous studies that have primarily focused on isolated technical or cyber risks, this research develops a comprehensive framework that integrates technological, operational, economic, and resilience-related risk dimensions within the context of digitally transformed electricity supply chains. By combining qualitative thematic analysis with the SWARA multi-criteria decision-making method, the study provides a systematic approach for identifying and prioritizing smart supply chain risks while explicitly considering the implications of digital transformation technologies. From a practical perspective, the proposed framework offers electricity industry managers a structured decision-support tool for allocating resources, prioritizing risk mitigation strategies, and improving supply chain resilience through data-driven decision-making. The framework also supports the implementation of digital transformation initiatives by enabling organizations to identify critical vulnerabilities and make more informed strategic decisions in increasingly interconnected and intelligent energy ecosystems.

Figure 1 illustrates the theoretical framework underpinning this study by explaining how digital transformation technologies influence both the capabilities and the risk profile of electricity supply chains. The framework assumes that the adoption of digital technologies, including artificial intelligence, the Internet of Things (IoT), blockchain, digital twins, and big data analytics, enhances the operational capabilities of smart supply chains through real-time monitoring, data integration, predictive analytics, intelligent decision support, and process automation. These capabilities improve supply chain visibility, operational flexibility, coordination among stakeholders, and the ability to respond rapidly to disruptions. Consequently, digital transformation serves as an important enabler of supply chain resilience and supports more effective and data-driven managerial decision-making in the electricity industry.

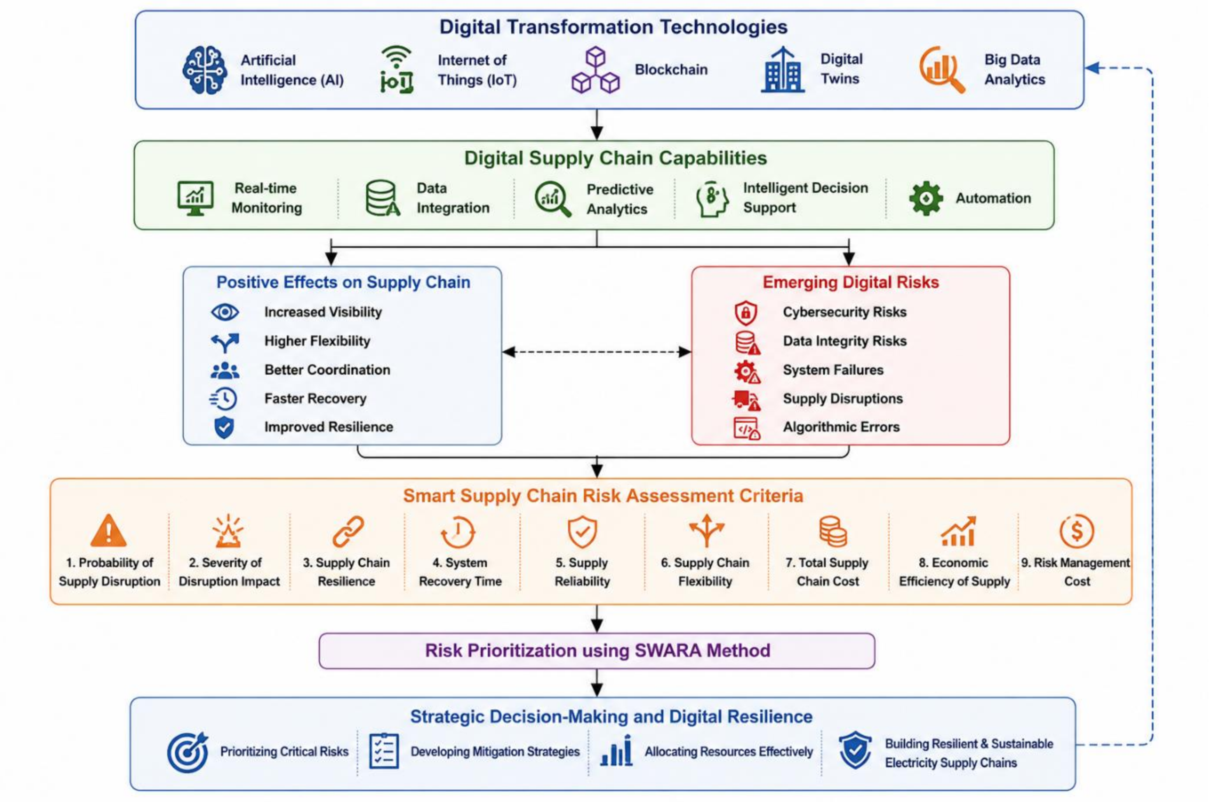

***Figure 1.*** *Illustration of the theoretical framework*

At the same time, the framework recognizes that digital transformation introduces new categories of risks alongside its operational benefits. Increased dependence on interconnected digital infrastructures exposes electricity supply chains to cybersecurity threats, communication failures, data integrity problems, algorithmic errors, and cascading disruptions across network components. These emerging risks directly influence critical supply chain performance dimensions, including disruption probability, disruption severity, recovery time, supply reliability, supply chain flexibility, economic efficiency, and risk management costs. Accordingly, this study employs the SWARA method to prioritize these multidimensional risks and provide a structured decision-support framework for identifying critical vulnerabilities and guiding strategic investments toward more resilient, intelligent, and sustainable electricity supply chains.

## Method

In this study, the research approach is of a mixed type (qualitative-quantitative) and is applied-developmental in terms of purpose. In the first step, using the qualitative fuzzy Delphi method, the risks of the smart supply chain in the electricity industry are identified and screened. The expert community includes electricity industry experts, supply chain managers, and university professors in the field of energy management and digital transformation technologies, who are selected using a purposive sampling method. In the Delphi stage, during several rounds of questionnaires, the opinions of the experts about the importance and effectiveness of the risks are collected and, using fuzzy logic, the uncertainty in human judgments is modeled and converted into analyzable values. The goal of this stage is to reach a relative consensus among the experts and extract the final set of key risks that affect the smart electricity supply chain. In the second stage of the research, the Step-wise Weight Assessment Ratio Analysis (SWARA) method is used to weight and rank the identified risks. This method is a multi-criteria decision-making technique that operates based on the relative importance of criteria and their step-by-step comparison. In this step, experts first rank the risks based on importance from the most important to the least important, and then the importance ratio of each criterion to the previous criterion is determined. Using these ratios, the final weight of each risk is calculated and finally, the prioritization of smart supply chain risks in the electricity industry is performed. The main advantage of the Swara method over other methods such as AHP is the reduction of the complexity of pairwise comparisons and the increase in the accuracy of weighting, especially when the number of criteria is large and there is high uncertainty. The results from Fuzzy Delphi and Swara are combined and a comprehensive model for assessing and ranking smart supply chain risks in the electricity industry is presented. This model allows the identification of key risks such as cyber, technological, operational, regulatory and environmental risks and prioritizes them based on the final weight. To increase the validity of the research, content validity tests (CVR and CVI) and reliability of expert opinions are also used. Finally, the output of this research can be used as a decision-making tool for electricity industry managers to focus their limited resources on higher-priority risks and increase the resilience of the smart supply chain against threats arising from digital transformation (Zavadskas et al., 2022; Yıldırım & Saaty, 2023).

The Fuzzy Delphi and SWARA methods were selected because they are well suited to the objectives and characteristics of this study. The Fuzzy Delphi method was employed to identify and validate supply chain risk criteria under conditions of uncertainty, as it effectively captures expert knowledge while reducing ambiguity and subjectivity through fuzzy linguistic judgments. Compared with the traditional Delphi technique, the fuzzy extension provides greater robustness in situations where experts express imprecise or qualitative opinions. Subsequently, the SWARA method was adopted to determine the relative importance of the validated criteria because it enables experts to assign weights through a simple, transparent, and sequential evaluation process without requiring extensive pairwise comparisons. Unlike methods such as AHP or ANP, which become computationally complex as the number of criteria increases, SWARA is particularly suitable for studies involving expert-based prioritization with a moderate number of evaluation criteria. Therefore, the combination of Fuzzy Delphi for criterion identification and validation and SWARA for criterion weighting provides a systematic, reliable, and practical framework for assessing smart supply chain risks in the context of digital transformation in the electricity industry

## Findings

### *Delphi Method*

The qualitative phase of this study involved 30 experts selected through purposive sampling based on their professional knowledge and practical experience in electricity supply chain management, digital transformation, and risk management. The inclusion criteria required participants to possess substantial expertise in at least one of these domains, hold managerial, technical, or academic positions, and have a minimum of five years of relevant professional experience. Among the participants, 21 (70%) were male and 9 (30%) were female.

Regarding educational background, 6 experts (20%) held a bachelor's degree, 13 (43.3%) held a master's degree, and 11 (36.7%) held a doctoral degree in fields related to industrial engineering, electrical engineering, supply chain management, information technology, or business management.

In terms of professional experience, 8 experts (26.7%) had 5–10 years of experience, 12 (40.0%) had 11–15 years, and 10 (33.3%) had more than 15 years of experience in the electricity industry or related digital transformation projects. The diversity of participants in terms of educational qualifications, professional roles, and years of experience enhanced the credibility and comprehensiveness of the expert judgments used throughout the Delphi and SWARA processes.The notation of the components is given in Table 1:

***Table 1.*** *Identified Components*

| Symbol | Component | CVI | CVR |
|---|---|---|---|
| S01 | Probability of supply disruption | 0.94 | 0.89 |
| S02 | Severity of disruption impact | 0.97 | 0.94 |
| S03 | Supply chain resilience | 0.99 | 1.00 |
| S04 | System recovery time | 0.93 | 0.83 |
| S05 | Supply reliability | 0.96 | 0.94 |
| S06 | Supply chain flexibility | 0.95 | 0.89 |
| S07 | Total supply chain cost | 0.91 | 0.78 |
| S08 | Economic efficiency of supply | 0.92 | 0.83 |
| S09 | Risk management cost | 0.90 | 0.72 |

The seven-degree fuzzy spectrum for index valuation is shown in Table 2.

***Table 2.*** *Seven-degree fuzzy spectrum for index valuation*

| Fuzzy number scale | Fuzzy value | Linguistic variable |
|---|---|---|
| (0, 0, 0.1) | $\tilde{1}$ | Not at all important |
| (0, 0.1, 0.3) | $\tilde{2}$ | Very important |
| (0.1, 0.3, 0.5) | $\tilde{3}$ | Unimportant |
| (0.3, 0.5, 0.75) | $\tilde{4}$ | Moderately important |
| (0.5, 0.75, 0.9) | $\tilde{5}$ | Very important |
| (0.75, 0.9, 1) | $\tilde{6}$ | Very important |
| (0.9, 1, 1) | $\tilde{7}$ | Linguistic variable |

***a) First round of Delphi technique***

The views of 10 experts on each indicator are shown in Table 3:

***Table 3.*** *Fuzzification of the expert panel's views for each of the research indicators*

| Items | Expert 1 | Expert 2 | Expert 3 | ... | Expert 10 |
|---|---|---|---|---|---|
| S01 | (0.9, 1, 1) | (0.5, 0.75, 0.9) | (0.9, 1, 1) | ... | (0.9, 1, 1) |
| S02 | (0.5, 0.75, 0.9) | (0.9, 1, 1) | (0.3, 0.5, 0.75) | ... | (0.9, 1, 1) |
| S03 | (0.75, 0.9, 1) | (0.5, 0.75, 0.9) | (0.75, 0.9, 1) | ... | (0.75, 0.9, 1) |
| S04 | (0.75, 0.9, 1) | (0.5, 0.75, 0.9) | (0.1, 0.3, 0.5) | ... | (0.75, 0.9, 1) |
| S05 | (0.5, 0.75, 0.9) | (0.1, 0.3, 0.5) | (0.5, 0.75, 0.9) | ... | (0.9, 1, 1) |
| S06 | (0.75, 0.9, 1) | (0.3, 0.5, 0.75) | (0.9, 1, 1) | ... | (0.5, 0.75, 0.9) |
| S07 | (0.75, 0.9, 1) | (0.5, 0.75, 0.9) | (0.9, 1, 1) | ... | (0.9, 1, 1) |
| S08 | (0.75, 0.9, 1) | (0.5, 0.75, 0.9) | (0.75, 0.9, 1) | ... | (0.9, 1, 1) |
| S09 | (0.5, 0.75, 0.9) | (0.3, 0.5, 0.75) | (0.5, 0.75, 0.9) | ... | (0, 0, 0.1) |

In the next step, the experts' views should be aggregated. Various methods have been proposed to aggregate the opinions of n respondents. In fact, these aggregation methods are empirical methods that have been presented by various researchers. For example, a common method for aggregating a set of triangular fuzzy numbers is to consider the minimum l, the geometric mean m, and the maximum u.

Equation 1

$$F_{AGR} = \left(min\{l\}, \prod\{m\}, max\{u\}\right)$$

Equation 2

$$F_{AGR} = \left(min\{l\}, \left\{\frac{\sum m}{n}\right\}, max\{u\}\right)$$

Equation 3

$$F_{AVE} = \left(\left\{\frac{\sum l}{n}\right\}, \left\{\frac{\sum m}{n}\right\}, \left\{\frac{\sum u}{n}\right\}\right)$$

Each triangular fuzzy number resulting from the aggregation of expert opinions for the jth index is shown as follows:

$$\tau_j = \left(L_j , M_j , U_j\right)$$

$$L_j = \min\left(X_{ij}\right)$$

$$M_j = \sqrt[n]{\prod_{i=1}^{n} X_{ij}}$$

$$U_j = \max\left(X_{ij}\right)$$

Index *i* refers to the expert. So that

$X_{ij}$: the i-th expert evaluation value of the j-th criterion

$L_j$: the minimum value of evaluations for the $j$-th criterion

$M_j$ : the geometric mean of the experts' evaluation values of the j-th criterion

$U_j$: the maximum value of evaluations for the $j$-th criterion

In this study, we have used the fuzzy mean method.

***Defuzzification of values***

Usually, the average of triangular and trapezoidal fuzzy numbers can be summarized by a definite value that is the best corresponding average. This operation is called defuzzification. There are several methods for defuzzification. In most cases, the following simple method is used for defuzzification:

Relation 4

$$x_m^1 = \frac{L+M+U}{3}$$

Another simple method for defuzzifying the mean of triangular fuzzy numbers is as follows:

Relation 5

$$F_{ave} = (L\,,M\,,U)$$

$$x_m^2 = \frac{L+2M+U}{4}\,;\; x_m^3 = \frac{L+4M+U}{6} x_m^1 = \frac{L+M+U}{3}\,;$$

$$\text{Crisp number} = Z* = \max\left(x_{max}^1\,,x_{max}^2\,,x_{max}^3\right)$$

The values of $x_{max}^i$ do not differ much and are always a number close to M. M is the average of the possible values of m of different triangular fuzzy numbers. However, the definitive value of the largest calculated $x_{max}^i$ is considered (Bujadzev and Bujadzev, 2007).

In this study, the center of the surface method is used for defuzzification as follows:

Relation 6

$$DF_{ij} = \frac{\left[\left(u_{ij}-l_{ij}\right)+\left(m_{ij}-l_{ij}\right)\right]}{3} + l_{ij}$$

The fuzzy mean and defuzzified output of the values of the indicators are given in Table 4. A defuzzified value greater than 7 is accepted and any indicator with a score less than 7 is rejected.

***Table 4.*** *Results of screening indicators (first round)*

| Round 1 Result | Definite value | Fuzzy Mean | Upper bound | probable value | Lower bound | Indicators |
|---|---|---|---|---|---|---|
| Accept | 0.778 | (0.646,0.798,0.89) | 0.890 | 0.798 | 0.646 | S01 |
| Accept | 0.738 | (0.604,0.754,0.854) | 0.854 | 0.754 | 0.604 | S02 |
| Accept | 0.741 | (0.569,0.756,0.898) | 0.898 | 0.756 | 0.569 | S03 |
| Accept | 0.777 | (0.623,0.796,0.913) | 0.913 | 0.796 | 0.623 | S04 |
| Accept | 0.813 | (0.681,0.833,0.923) | 0.923 | 0.833 | 0.681 | S05 |
| Accept | 0.803 | (0.66,0.825,0.923) | 0.923 | 0.825 | 0.660 | S06 |
| Accept | 0.928 | (0.833,0.956,0.996) | 0.996 | 0.956 | 0.833 | S07 |
| Accept | 0.890 | (0.771,0.917,0.983) | 0.983 | 0.917 | 0.771 | S08 |
| Accept | 0.741 | (0.569,0.756,0.898) | 0.898 | 0.756 | 0.569 | S09 |

All items with a score of less than 0.7 are eliminated, which shows that no items were eliminated.

b) Round Two of the Delphi Technique

The fuzzy Delphi analysis continued for the remaining indicators in the second round. In this stage, 34 indicators were evaluated based on the views of 10 experts. The results of the fuzzy Delphi in the second round are reported in Table 5:

***Table 5.*** *Fuzzy Mean and Fuzzy Screening of Indicators (Round Two)*

| Round 2 Result | Definite value | Fuzzy Mean | Upper bound | probable value | Lower bound | Indicators |
|---|---|---|---|---|---|---|
| Accept | 0.795 | (0.673,0.815,0.898) | 0.898 | 0.815 | 0.673 | Q01 |
| Accept | 0.806 | (0.692,0.827,0.9) | 0.900 | 0.827 | 0.692 | Q02 |
| Accept | 0.790 | (0.631,0.81,0.929) | 0.929 | 0.810 | 0.631 | Q03 |
| Accept | 0.853 | (0.723,0.877,0.958) | 0.958 | 0.877 | 0.723 | Q04 |
| Accept | 0.852 | (0.729,0.877,0.95) | 0.950 | 0.877 | 0.729 | Q05 |
| Accept | 0.808 | (0.663,0.831,0.929) | 0.929 | 0.831 | 0.663 | Q06 |

| Round 2 Result | Definite value | Fuzzy Mean | Upper bound | probable value | Lower bound | Indicators |
|---|---|---|---|---|---|---|
| Accept | 0.908 | (0.8,0.935,0.988) | 0.988 | 0.935 | 0.800 | Q07 |
| Accept | 0.890 | (0.769,0.915,0.988) | 0.988 | 0.915 | 0.769 | Q08 |
| Accept | 0.790 | (0.631,0.81,0.929) | 0.929 | 0.810 | 0.631 | Q09 |

### *End of Delphi Rounds*

No questions were eliminated in the second round, which is a sign of the end of the Delphi rounds. In general, one approach to ending a Delphi is to compare the average scores of the questions from the first and second rounds. If the difference between the two stages is less than a very small threshold (0.2), then the survey process is stopped.

***Table 6.*** *The difference between the first and second round's final values*

| Result | Difference | Round 2 Result | Round 1 Result | Indicators |
|---|---|---|---|---|
| Agreement | 0.017 | 0.795 | 0.778 | Q01 |
| Agreement | 0.069 | 0.806 | 0.738 | Q02 |
| Agreement | 0.049 | 0.790 | 0.741 | Q03 |
| Agreement | 0.076 | 0.853 | 0.777 | Q04 |
| Agreement | 0.040 | 0.852 | 0.813 | Q05 |
| Agreement | 0.005 | 0.808 | 0.803 | Q06 |
| Agreement | 0.021 | 0.908 | 0.928 | Q07 |
| Agreement | 0.000 | 0.890 | 0.890 | Q08 |
| Result | 0.049 | 0.790 | 0.741 | Q09 |

Based on the results in Table 6, it was determined that in all cases the difference is smaller than 0.2, so the Delphi rounds can be completed.

At the conclusion of the third Delphi round, the level of agreement among the panel of experts was assessed using Kendall's coefficient of concordance (Kendall's W). The results indicated a Kendall's W value of 0.81, with the test reaching a high level of statistical significance ($p < 0.001$), demonstrating a strong degree of consensus and convergence among the experts regarding the proposed model indicators. Furthermore, the negligible changes observed in the mean ratings and interquartile ranges of the indicators compared with the previous Delphi round suggest that both theoretical saturation and an acceptable level of consensus had been achieved. Consequently, the Delphi process was terminated after the third round, and the validated indicators were retained as the final dimensions of the conceptual model for subsequent analysis and validation.

### *SWARA Method*

SWARA (Step-Wise Weight Assessment Ratio Analysis) Method means Gradual Weighting Evaluation Ratio Analysis Method. SWARA Method is one of the new multi-criteria decision-making methods introduced in 2010 by Violeta Keršalinė together with Zavadskas and Tūrskis. This method is used to calculate the weight of the criteria.

In Swara Method, experts first arrange the criteria in order of importance. The most important criterion is placed first and gets a score of one. Finally, the criteria are ranked based on the average values of relative importance.

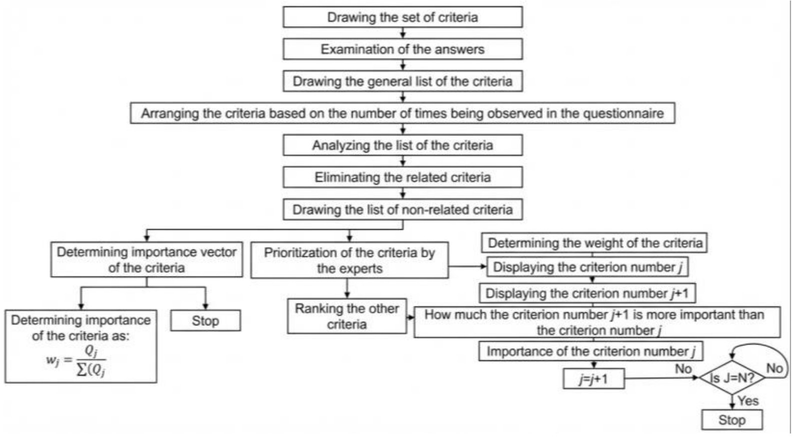

***Figure 2.*** *Steps of the SWARA method (Karshaline et al., 2010)*

***Step 1: Sorting the criteria***

First, the criteria are written in order of importance. The most important criteria are placed in higher ranks and the less important criteria are placed in lower ranks.

***Step 2: Determining the relative importance of each criterion ($S_j$)***

In this step, the relative importance of each criterion compared to the previous criteria is determined. In the SWARA method process, this value is represented by $S_j$.

***Step 3: Calculating the $K_j$ coefficient***

The $K_j$ coefficient, which is a function of the relative importance of each criterion, is calculated using equation 1:

$K_j = S_j + 1$

***Step 4: Calculating the initial weight of each criterion***

The initial weight of the criteria is calculated using equation 2. In this regard, it should be noted that the weight of the first criterion, which is the most important criterion, is considered equal to 1.

$$Q_j = \frac{Q_{j-1}}{K_j}$$

$Q_j = Q_j$-1 / $K_j$

***Step 5: Calculating the final normal weight***

In the last step of the SWARA method, the final weight of the branches, which is also considered the normalized weight, is calculated through equation 3. Normalization is performed using a simple linear method.

$$W_j = \frac{Q_j}{\sum Q_j}$$

As mentioned, the main feature of the SWARA method is that it is possible to evaluate the opinions of experts or evaluation groups regarding the importance of the indicators in the process of determining their weight.

***Prioritizing the indicators identified by the SWARA method***

The indicators identified by the SWARA method are prioritized. In the SWARA method, experts first arrange the criteria in order of importance. The most important criterion is placed first and receives a score of one. Finally, the identified indicators are ranked based on the average values of relative importance. First, the identified indicators are arranged according to their importance. Then, the relative importance of each criterion compared to the previous criteria is determined. These values are included in the “Average Relative Importance” column in Table 1, which is ($S_i$).

In the third step of the SWARA method, the coefficient ($K_{i)}$ is calculated. The coefficient ($K_i$) for the multi-objective model index for evaluating non-dominant solutions to electricity industry supply chain risks, which is of the greatest importance, is one. This value has also been calculated for other identified indicators. To calculate the initial weight of each criterion, the following equation has been calculated.

$$Q_i = \frac{Q_{i-1}}{K_i}$$

$$Q_1 = 1$$

$$Q_2 = \frac{Q_1}{K_2} = \frac{1}{1.24} = 0.806$$

$$Q_3 = \frac{Q_2}{K_3} = \frac{0.806}{1.31} = 0.616$$

These values are included in the “Initial Weight” column in Table 7. To calculate the final weight, the linear normalization method has been used according to the following equation.

$$W_i = \frac{Q_i}{\sum Q_i}$$

In this way, the final weight of each element is obtained.

***Table 7.*** *Prioritization of indicators identified by the Swara method*

| Normal weight | Initial weight | Kj | Medium Relative Importance | Criterion Code |
|---|---|---|---|---|
| 0.232 | 1 | 1 | 1 | S01 |
| 0.176 | 0.758 | 1.32 | 0.32 | S02 |
| 0.136 | 0.587 | 1.29 | 0.29 | S03 |
| 0.109 | 0.47 | 1.25 | 0.25 | S04 |
| 0.091 | 0.392 | 1.20 | 0.20 | S05 |
| 0.077 | 0.332 | 1.18 | 0.18 | S06 |
| 0.066 | 0.286 | 1.16 | 0.16 | S07 |
| 0.058 | 0.251 | 1.14 | 0.14 | S08 |
| 0.053 | 0.228 | 1.10 | 0.10 | S09 |
| 1.000 | 6.757 | Total | | |

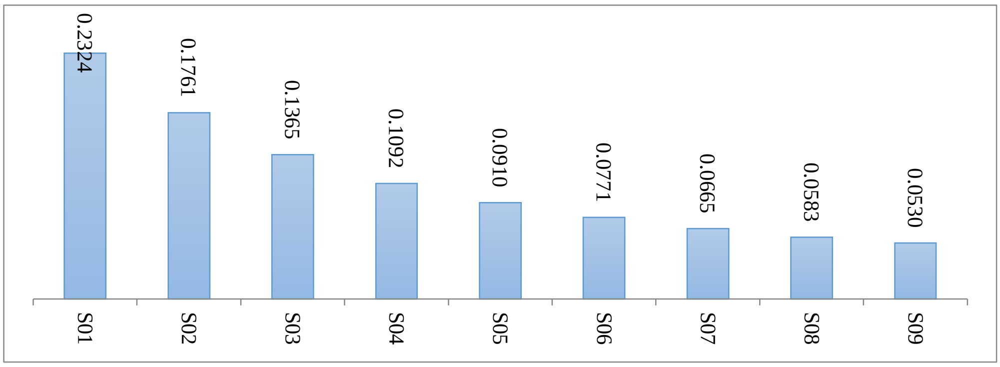

***Figure 3.*** *Final weight of indicators identified by the Swara method*

Probability of supply disruption with a weight of 0.232 is in the first priority. Severity of disruption impact with a weight of 0.176 is in the second priority. Supply chain resilience with a weight of 0.136 is in the third priority. System recovery time with a weight of 0.109 is in the fourth priority. Supply reliability with a weight of 0.091 is in the fifth priority. Supply chain flexibility with a weight of 0.077 is in the sixth priority. Total supply chain cost with a weight of 0.066 is in the seventh priority. Economic efficiency of supply with a weight of 0.058 is in the eighth priority. Risk management cost with a weight of 0.053 is in the ninth priority.

The results of the SWARA analysis indicate that S01 received the highest normalized weight (0.232), demonstrating that it is the most influential criterion in assessing smart supply chain risks in the electricity industry. This finding suggests that experts considered this criterion to have the greatest impact on supply chain performance under conditions of digital transformation. S02 ranked second with a normalized weight of 0.176, followed by S03 with 0.136. Collectively, these three criteria account for more than half of the total normalized weight, highlighting that decision-makers should primarily focus on these factors when designing risk mitigation strategies and allocating organizational resources.

The remaining criteria exhibited a gradual decline in importance, reflecting the sequential weighting mechanism of the SWARA method. Specifically, S04 (0.109), S05 (0.091), and S06 (0.077) represent criteria of moderate importance that contribute to strengthening the operational resilience and continuity of the electricity supply chain. Their corresponding comparative importance coefficients (Kj) ranged from 1.18 to 1.25, indicating that experts perceived these criteria as progressively less influential than the preceding ones while still recognizing their meaningful contribution to comprehensive risk management. Similarly, S07 (0.066), S08 (0.058), and S09 (0.053) received relatively lower weights, suggesting that although these factors remain relevant, they are considered secondary priorities within the overall risk assessment framework.

Overall, the SWARA results demonstrate a clear prioritization pattern in which the greatest emphasis is placed on the prevention and management of high-impact supply chain risks, followed by criteria related to operational resilience and, finally, economic considerations. The total initial weight of 6.757 and the normalized weights summing to 1.000 confirm the internal consistency of the weighting process. From a managerial perspective, these findings imply that organizations operating in the electricity industry should prioritize investment in the highest-ranked risk factors while maintaining balanced attention to operational and economic dimensions. Such an approach can enhance supply chain resilience, support more effective resource allocation, and improve strategic decision-making within digitally transformed electricity supply chains.

## Discussion

The findings from the SWARA method show that in the electricity supply chain, experts have focused more on the risks associated with “supply disruption” and its consequences, while economic criteria have been given lower priority. This result is in line with the modern literature on supply chain management, which emphasizes that in critical infrastructure industries such as energy, “service continuity” and “operational resilience” have priority over cost optimization. Recent studies have shown that in critical supply chains, decision-making has moved towards reducing vulnerability and increasing survivability in crisis situations, even if this leads to increased short-term costs (Ivanov & Dolgui, 2022; Kamble et al., 2024). Therefore, the dominance of risk-based criteria in this study indicates a paradigm shift from mere economic efficiency to system security and sustainability.

Based on the results, “probability of supply disruption” was identified as the most important criterion with a weight of 0.232. This finding shows that, in the eyes of experts, the starting point for risk management in the electricity industry is to control potential sources of supply disruption. In fact, any weakness in the supplier network, over-reliance on limited resources, or vulnerability in logistics infrastructure can increase the likelihood of disruption. Recent literature also emphasizes that in smart supply chains, especially in the energy industry, risks arising from supply disruption have been exacerbated by digitalization and globalization (Sá et al., 2023). From this perspective, the results of this study indicate that risk management strategies should focus on supplier diversification, smart chain monitoring, and the use of data-driven predictive technologies.

In second place is “severity of disruption impact” with a weight of 0.176. This result indicates that experts have not only considered the probability of risk occurrence, but also its potential consequences as a key factor. In the electricity industry, even short-term disruptions can lead to widespread outages, increased maintenance costs, and reduced network reliability. Recent studies in the field of critical infrastructure show that the severity of risk in such systems usually increases exponentially, creating domino effects throughout the network (Gholami et al., 2023). Therefore, the high importance of this criterion indicates the necessity of simultaneous “probability-consequence” analysis in the design of risk management models. The results also show that “supply chain resilience” ranks third with a weight of 0.136. This finding is consistent with the new literature on supply chain resilience, which defines it as the ability of a system to absorb shocks, adapt, and recover performance. In the smart electricity supply chain, resilience depends not only on the physical structure of the network but also on the digital infrastructure. Recent research emphasizes that resilience in the digital age is enhanced through the integration of technologies such as the Internet of Things, artificial intelligence, and real-time data analytics (Ivanov, 2023). Therefore, the high ranking of this criterion indicates the importance of the transition from reactive to proactive management in the electricity industry.

Next, “system recovery time” with a weight of 0.109 and “reliability of supply” with a weight of 0.091 are ranked fourth and fifth, respectively. These results indicate that in addition to preventing disruption, experts also pay attention to the system’s capacity to quickly return to a stable state. In the resilience literature, recovery time is considered one of the key performance indicators of critical systems, as its reduction directly reduces the economic and social impacts of disruption (Shekarian & Mellat Parast, 2021). Also, supply reliability, as the most basic feature of a sustainable supply chain, plays an important role in reducing uncertainty, although it has gained relative importance compared to more critical criteria.

In lower ranks, “supply chain flexibility” (0.077), “total supply chain cost” (0.066), “economic efficiency of supply” (0.058) and finally “risk management cost” (0.053) are ranked. This order shows that economic criteria are in the final priorities of the experts. This finding is in line with new trends in sustainable supply chain management, which show that in critical industries, economic criteria have taken a secondary role compared to safety and service continuity criteria (Chowdhury et al., 2021). In fact, organizations prefer to pay more to reduce risk and increase resilience in order to avoid the severe consequences of disruption.

Overall, the SWARA results show that the risk prioritization structure in the electricity industry has been formed as a “risk-based and resilience-based” one; in such a way that the probability and severity of disruption are considered first, then resilience capacities, and finally economic criteria. This pattern indicates a transition from traditional cost-based approaches to resilience-based approaches in the smart supply chain. Such results can be the basis for developing multi-objective decision-making models and designing solutions based on digital transformation technologies for risk management in the electricity industry.

The findings of this study extend beyond risk prioritization by demonstrating how digital transformation can enhance strategic supply chain management in the electricity sector. The identified priorities provide practical guidance for organizations seeking to integrate digital technologies into risk management processes, enabling more proactive decision-making, real-time monitoring, predictive analytics, and resilient supply chain operations. Therefore, the proposed framework contributes not only to the literature on supply chain risk assessment but also to the broader field of digital transformation by supporting the transition toward intelligent, data-driven, and sustainable supply chain ecosystems. Future research may further strengthen this perspective by integrating advanced digital technologies, such as digital twins, blockchain, and artificial intelligence, into dynamic supply chain risk assessment models.

## Conclusion

The findings of this study provide several practical implications for managers and policymakers in the electricity industry. The prioritization of smart supply chain risks enables managers to allocate financial and technological resources more effectively toward the most critical risk factors, particularly those related to supply disruptions and operational resilience. The results also support the implementation of digital transformation initiatives by highlighting the importance of integrating artificial intelligence, IoT, digital twins, and real-time monitoring systems into supply chain risk management. Furthermore, the proposed framework can serve as a decision-support tool for designing preventive maintenance strategies, improving supply reliability, reducing recovery time following disruptions, and strengthening organizational resilience. By adopting a structured and data-driven risk prioritization approach, electricity companies can enhance operational continuity, reduce unnecessary costs, and improve strategic decision-making in increasingly complex digital supply chain environments.

This study developed a systematic framework for identifying, evaluating, and prioritizing smart supply chain risks in the electricity industry by integrating qualitative thematic analysis with the SWARA multi-criteria decision-making method. The findings indicate that the probability of supply disruption, the severity of disruption impact, and supply chain resilience represent the most influential criteria affecting supply chain performance in digitally transformed electricity systems. These results emphasize that effective risk management requires not only reducing the likelihood of disruptions but also improving the ability of supply chains to adapt and recover rapidly.

From a practical perspective, the proposed framework provides electricity industry managers with a structured decision-support tool for prioritizing investments, strengthening digital infrastructure, improving supply chain resilience, and supporting data-driven strategic planning. The study also contributes to the literature on digital transformation by demonstrating how systematic risk prioritization can facilitate the development of intelligent, resilient, and sustainable electricity supply chains capable of responding effectively to emerging technological and operational challenges.

Despite its contributions, this study has several limitations. First, the identification and prioritization of risk criteria relied primarily on expert judgments, which may involve subjective evaluations despite the application of the Delphi technique and structured weighting procedures. Second, the study was conducted within the context of the electricity industry, and therefore the findings may not be directly generalizable to other industrial sectors with different operational characteristics. Third, the SWARA method assumes conceptual independence among evaluation criteria and does not explicitly model potential interdependencies or causal relationships between risks. These limitations should be considered when interpreting the results.

### *Future Research*

Future studies may extend the proposed framework by incorporating advanced multi-criteria decision-making methods capable of modeling interdependencies among risk factors, such as ANP, DANP, or DEMATEL. Researchers may also validate the proposed model in other sectors, including oil and gas, renewable energy, manufacturing, healthcare, and transportation, to examine its generalizability. Furthermore, integrating real-time operational data, machine learning algorithms, digital twins, blockchain, and big data analytics into dynamic risk assessment models could improve the accuracy and adaptability of supply chain risk management. Comparative studies across different countries and electricity market structures would also provide valuable insights into the influence of regulatory and technological environments on smart supply chain risk prioritization.

## Declaration of Competing Interest

The author declares that he has no competing financial interests or known personal relationships that would influence the report presented in this article.

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